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Cost analysis for removal of VOCs from water by pervaporation using NSGA-II

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ABSTRACT

The single-objective optimization study by Satyanarayana and Bhattacharya (2003) [1] on removal of volatile organics from aqueous solution by single stage pervaporation without recycling has been extended by treating it as a multi-objective optimization problem. The various costs of the process namely-initial capital cost, feed pumping cost, vacuum and condensation cost and membrane replacement cost constitute the objective functions. The present work attempts to explore the pervaporation process economics by employing artificial intelligence method of non-dominated sorting genetic algorithm-II (NSGA-II). The cost of feed pumping offers significant trade-off with the costs of initial capital or vacuum and condensation. Although to a lesser extent, the trade-offs are also available between the costs of initial capital and vacuum and condensation. The results from this study clearly establish that the major costs for removal of volatile organics from water are feed pumping, initial capital, and vacuum and condensation.

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1. Introduction

Volatile organic compounds (VOCs) like aldehydes, ketones and hydrocarbons, which exhibit a vapor pressure of about 1 mm of Hg at 25 °C, can cause global warming, leukemia and respiratory problems. Huge expenses are incurred globally for waste water treatment. Removal of VOCs from waste water is the main and costly process in the waste water treatment. A number of technologies [2–6] have been tried with an objective to reduce the cost of this process. Each method has shown its advantages and disadvantages [4] and there remains a definite need for a cost-effective removal of VOCs from waste water. To achieve this object, we have tried to analyze the cost of removal of VOCs from water by using an advanced separation process like pervaporation in this study.

Pervaporation is a membrane based separation process in which feed solution is brought in contact with one side of the membrane and permeate is removed from the other side of the membrane by applying a pressure lower than the saturation vapor pressures of the components. Pervaporation is not only a cleaning technology but also a clean technology, with added advantage of lesser treatment cost for separation of multi-component VOCs compared to that of a binary mixture [1].

Some of the reported works on removal of VOCs from water explored new membrane materials and surface modifications of membranes [7], module designs [8], hybridizations [9] and concentration polarization [10]. A comprehensive review on removal of VOCs by pervaporation process is done by Peng et al. [11]. However, not much work has been reported on optimization and cost analysis. Therefore, the main objective of the present study was to perform a thorough cost analysis on removal of VOCs from multi-component aqueous solutions using multi-objective optimization.

Earlier a pervaporation model was developed for separation of VOCs from waste water and the optimum process conditions were determined for separation of a binary mixture [12]. The same model was extended [1] for multi-component aqueous solutions and the minimization of treatment cost for removal of toluene from a four component aqueous mixture was studied.

Carrying out a single objective optimization of the treatment cost by assigning fixed unit prices (preferences or weighting factors) [1] to various costs that contribute to it would restrict the applicability of solution to a specific case. In addition, any set of unit prices assigned to various costs might miss some of the solutions especially when non-convexity of the problem gives rise to duality gap [13–15]. Further, the e-constraint method has the disadvantage that the solution obtained is specific to the objective function chosen and the limits set to the constraints that are obtained by converting the remaining objectives of the problem. Hence one may solve the problem as multi-objective optimization [16]. However, a multi-objective optimization problem is often set up when the objectives are not easily comparable or non-commensurate. An excellent review by Bhaskar et al. [17] presents several of multi-objective optimization problems set up in the past in core chemical engineering. Several advantages are offered by the NSGA-II algorithm [13]. Therefore, in the present study the NSGA-II

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algorithm is employed for cost analysis. The previously available process and cost models useful for study are outlined in Appendix 1 and Appendix 2 respectively [1].

Treatment cost is mainly composed of the costs of: 1. capital depreciation; 2. maintenance and labor; 3. membrane replacement; and 4. energy. Further, it is clear from the cost model that the energy cost consists of vacuum and condensation cost and feed pumping cost.

Prima facie it appears that the initial capital cost and energy costs can be further split in to different costs and a multi-objective optimization of higher dimension can be carried out. But to reduce the complexity of the problem and to make it a physically meaningful and comprehensive analysis, the four major costs (initial capital cost, membrane replacement cost, vacuum and condensation cost, and feed pumping cost) have been chosen for minimization. For example, capital depreciation cost and maintenance and labor costs can be merged in to one single cost for following reasons. The trade-offs available for other costs are not so attractive when these two are considered as independent costs. The cost model shows fixed percentages (weighting factors) were given to above two costs based on the initial capital investment. Another example is the vacuum and condensation and the feed pumping costs are shown as two different objectives. Here it may appear that these two costs can be merged and taken as a single cost. But it would be more meaningful to treat them as different costs as both of them have emerged as significant costs of same order.

In addition, these four costs are conflicting in decision variable space. In other words, the cardinality of the Pareto optimal set is not one, which is the fundamental requirement to arrive at the non-dominated optimal solution set of the multi-objective optimization problem [16]. Hence, the objective of the present study is to carry out the multi-objective optimization or vector optimization for removal of VOCs from waste water by pervaporation while taking initial capital cost, membrane replacement cost, vacuum and condensation cost and feed pumping cost as objectives.

2. Theory and numerical simulation

The basic concept of the multi-objective optimization is to find a set of solutions called non-dominated set such that none of the solutions dominates any other solution (as there is no single solution that is the best with respect to all the objectives in the entire search space). In other words, as one moves from one point to the other of the Pareto optimal solutions in the objective function space, at least one of the objectives must be improving with simultaneous deterioration of at least one of the other objectives. These are also called the Pareto optimal solutions or Pareto optimal set. If the Pareto optimal set is such that if any other solution in the entire search space is dominated by at least one solution in the set then it is called the global Pareto optimal set.

NSGA-II is employed to obtain the trade-off solutions of the present problem. NSGA-II is based on the principle of natural evolution. A set of (given number of) random population is created initially. Each population is a string consisting of one value each of all the decision variables. The initial population is chosen randomly from the entire search space. In NSGA-II, the spread of the solutions is encouraged by assigning highest fitness to the most isolated solutions and lowest fitness to the most crowded solution.

NSGA-II algorithm is briefly outlined as follows: a given number of populations are generated randomly in the decision variable space. The population is divided in to several arbitrary number of non-dominating fronts based on the objective function values. Each of these fronts is assigned a common fitness value with the highest non-dominant set being given highest fitness value and the least dominating front being given the lowest, progressively. Then the fitness of each member of a given non-dominant set is estimated by dividing the fitness value of the set by the niche count of the member. The niche count of a member is a measure of number of solutions in its vicinity. The more crowded a particular member is the more will be its niche count and hence the lesser will be its fitness in a given front. Further, the most isolated member of the most dominant set is assigned with highest fitness and the most crowded solution in the lowest front is assigned the least fitness. This helps the spread of solutions in the Pareto set. Then the reproduction, cross over and mutation are carried out to produce evolved population. A set number of such evolutions are carried out to get the final solution. The detail description of NSGA-II algorithm is given by Deb [16].

Table 1
GA parameters chosen for optimization.

Maximum number of generations	500
Maximum population size	80
Probability of cross over	0.6
Probability of mutation	0.06
Random seed	0.0625
Distribution index for cross over	5
Distribution index for mutation	80

Hence the four objective optimization problems can be described as follows.

min Initial capital cost $(q, Re, l, p, x_{Tol}, x_{TCE}, x_{MC})$
min Membrane replacement cost$(q, Re, l, p, x_{Tol}, x_{TCE}, x_{MC})$
min Vacuum and condensation cost $(q, Re, l, p, x_{Tol}, x_{TCE}, x_{MC})$
min Feed pumping cost $(q, Re, l, p, x_{Tol}, x_{TCE}, x_{MC})$
s.t.

$$2.77\times10^{-3}<q<5.77\times10^{-3}$$
$$20<Re<2100$$
$$5\times10^{-6}<l<10^{-4}$$
$$0.2<p<4.0$$
$$2\times10^{-6}<x_{Tol}<9.8\times10^{-5}$$
$$2\times10^{-6}<x_{TCE}<9.7\times10^{-5}$$
$$2\times10^{-6}<x_{MC}<4.01\times10^{-3}$$

The solutions are obtained for 90% removal of toluene present in the feed solution. The trade-off solution obtained by genetic algorithms for a given problem is critical to the genetic parameters chosen. Further, a priori knowledge of the genetic parameters to be used in a given problem is impossible. However, the genetic parameters may be fixed by keeping in view of the two basic tasks [16] of multi-objective optimization. One task is to obtain the optimal solutions as close to the true Pareto-optimal region as possible and the other task is to maintain the spread of solutions with least scatter possible. For the present case, it is found that the number of generations, mutation and cross over probabilities are the important genetic parameters that affected the performance of the NSGA II. The values of genetic parameters chosen for present problem are given in Table 1.

As mentioned in the introduction the objective of the present work is to carry out the multi-objective optimization or vector optimization for removal of VOCs from waste water in a single stage pervaporation without recycling of permeate by extending the single-objective optimization study [1]. Therefore, process and cost models as well as the properties used for simulations are available elsewhere [1]. However, for easy understanding and to maintain the continuity some of the important equations used for simulation are reproduced below.

Overall continuity equation

$$\frac{1}{2\pi}\frac{dq}{dz}=-\sum_{i=1}^{3}\frac{L_{P,i,m}}{(E_i+1)}\frac{(x_iH_i-py_i/\rho)}{\ln(1+l/r_i)}-\frac{L_{P,w}}{\rho}\frac{(p_w^o-py_w)}{\ln(1+l/r_i)} \tag{1}$$

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